State of the art on the integration of dynamic traffic assignment and activity based models

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Abstract: *The analysis of heavily loaded transportation networks requires continuous development of transportation models. The current state of the practice is to use static transportation models, even though they date from the 1950's when congestion levels, economic and social activity patterns were radically different than today. In response to this, Activity-Based Modelling (ABM) and Dynamic Traffic Assignment (DTA) have been developed on parallel tracks. However, it is obvious that there is an interaction between activity scheduling and time-varying traffic conditions. The shortcomings of DTA and ABM may be solved by integrating the two facets, but only few researchers have explored the interface between DTA and ABM. This paper is an overview of the current state of the art on the integration of ABM and DTA, as well as the current developments on data gathering techniques for a combined model.*

Keywords: Activity-Based Models, Dynamic Traffic Assignment, Integration, New Data Sources, Literature Review

1. Introduction

The travel behaviour modeling problem can be, and has been, tackled from two directions. Firstly, transportation can be modeled by looking directly at traffic observations. Through behavioural assumptions like e.g. rationality, perception of costs and information about the traffic state, one can identify those patterns that are consistent with the traffic data. This is often referred to as (Dynamic) Traffic Assignment. The modeller focuses more on the mathematical description of trips and less on the reasons why a traveller makes these trips. Depending on the implementation of the DTA model, route choice, departure time choice or mode choice are also included. These sub models indicate the current virtual border of the DTA paradigm and the limitations of its capabilities. On the other hand, travel patterns can also be seen as a result of individuals' activity patterns and scheduling possibilities. ABM focuses on modelling activity patterns explicitly. This includes sub models for location choice and departure time choice among others.

It is clear that there exists some connection between these two modelling worlds. The demand and supply equilibrium is sometimes used to indicate this relation in macro-economic terms. It is however too simplistic to represent the connection. Both models rely on the formulation of some equilibrium encompassing the supply and demand.

In the next two chapters we briefly describe the two separate viewpoints of ABM and DTA. One of the biggest differences between the two modelling paradigms is the use of different data sources for calibrating the models. This issue will also be addressed in these two chapters. In the subsequent chapter the recent efforts in integrating ABM and DTA into a

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unified framework is discussed. Next a future research agenda is proposed that introduces novel data gathering techniques. This new data sources are necessary to close the gap between the DTA and ABM approaches. We focus on the description of a system to infer daily activity and trip patterns from smartphone sensor readings and the possible applications it has in the context of individual traffic managing.

2. Activity-Based Modelling

ABM captures the relation between activity patterns of a population, the scheduling of these activities in space and time and in result describes the demand for transportation services and networks. The conceptual appeal of this approach originates from the realization that the need and desire to participate in activities is more basic than the travel that some of these participations may entail (Bhat, 2003). ABM can in principle consider endogenously many interactions that are relevant for potential policy decisions such as transportation demand management, incentives for mode switches to public transportation, influence of social changes (demographic changes, women participation to labour, teleworking, flex working…) on transportation. Yet, in practice the influence of the level of service of transportation on activities is still oversimplified in current ABM applications. Moreover, ABM requires large, complex and expensive data collection on the characteristics, activities, preferences and sensitivities of different groups in the population.

In activity-based models, independence between activities is explicitly avoided to catch the relations between spatial and temporal distribution of activities and the transportation network. In other words, the activity-based approach aims at predicting which activities are conducted where, when, for how long, with whom, the transport mode involved and ideally also the implied route decisions (Zwerts, 2004). Currently, available activity-based models often neglect the resulting travel behavior, giving more focus and emphasis on within-day and day-to-day patterns related to activity location and (re)scheduling, while travel decisions are only treated as secondary elements (McNally, 2000). Moreover, congestion effects are mostly neglected, in order to guarantee model tractability. Examples of widely known activity-based models in practice are STARCHILD (Recker et al., 1986a, 1986b), SCHEDULER (Gärling et al., 1989), SAMS/AMOS (Kitamura et al., 1996) and ALBATROSS (Arentze et al., 2000). Trips and travel characteristics are in these models considered among the many attributes of an activity, often framed within complex nested choice models. Thus, it is difficult to gain insight into the real interdependencies between activities and travel choices. Due to the rather high complexity of activity-based models, characterized by extensive decision making 'trees', their integration into realistic transportation networks has been very limited.

ABM has been developed for policy analysis and demand forecasting, but they are difficult to calibrate for application in traffic state forecasting, mainly due to two reasons. First of all the number of parameters is often too large to obtain a significant estimate by calibration. This is a result of the data collection techniques used for this purpose. They are often based on stated preference surveys of a small sample of the population. It is expensive and hardly statistically valid. A second and more profound problem is to what extend ABM can be used to estimate local traffic conditions. ABM applications are usually micro-simulators implementing the multi-agent paradigm. The local traffic state is a manifestation of the interaction between the moving/traveling agents on a macroscopic level. In order to estimate the local traffic state, multiple simulation runs are needed. This is necessary to estimate the variation on the outcome and it has a large impact on calculation times. Finally, aggregated data of local traffic states is abundantly available and is used in practice only for validating ABM applications. This implies a gap between the microscopic estimation and the macroscopic validation which ABM still has to overcome.

3. Dynamic Traffic Assignment

Dynamic Traffic Assignment (DTA) is a set of criteria and rules through which the demand for mobility is distributed over time and space on a transportation network (Viti and Tampère, 2010). The role of DTA is, in essence, to model where, when and how a trip is made. Due to its well-acknowledged problem complexity, DTA theory has been mainly associated with route choice, while all other choice levels have been assumed exogenously given. However, many applications require other choice levels to be dealt with explicitly and simultaneously. Notwithstanding the importance of the other choice levels, empirical and theoretical findings have shown in particular that route and departure time choice have (at least) comparable dynamisms and strong correlations, and they must be modelled jointly, especially to understand the effects of e.g. congested networks, traffic information, dynamic pricing schemes and travel time variability (e.g., Mannering, 1989; Caplice and Mahmassani, 1992; Hatcher and Mahmassani, 1992; Khattak et al., 1995; Mahmassani and Liu, 1999; Szeto and Lo, 2004; Lim and Heydecker, 2005; Viti et al., 2005). Joint modelling of route–departure time choice also allows a more correct allocation of the total daily demand (Heydecker and Addison, 1998). The limitation of current route-departure time choice models stands in a rather "myopic" view of departure time choice making; this choice level has been treated often in a route choice-like manner (the well-known hypernetwork approach, Sheffi and Daganzo, 1979; Van der Zijpp and Lindveld, 2001), and often it has been developed using a single reference point, for instance the preferred arrival time (Abdelghany and Mahmassani, 2003) with the main goal of reproducing peak period spreading phenomena. Several studies (Small, 1982; Bowman and Ben-Akiva, 2001; Bhat et al., 2004) have also shown that growing concerns about congestion on the road network, and policies that are aimed at reducing it (e.g. road pricing), people tend to change their activity patterns, not only adjusting their time of departure. Therefore, a model capable of reflecting changes in individual activity schedules due to the conditions on the road network is required to accurately foresee the impact of policies aimed at reducing congestion (Adnan, 2010).

4. Integration of ABM and DTA

The shortcomings of DTA and ABM may be solved by integrating the two, taking care of extracting the relevant information, thus complying with the parsimony principle. To the best of our knowledge, there is very little research performing a real integration between activity-based models and DTA, while there is a wide recognition that these two modeling approaches, even if potentially complementing each other, have been developed rather independently (Lin et al., 2008). Only in the last decade this tendency has inverted and the interest in combining these two modeling approaches has grown. Recker (2001) formally showed the similarities between trip-based and activity-based models, and the opportunities that can arise in modeling day-to-day and within-day traffic dynamics. This was also shown by Lam and Yin (2001), who used temporal dependencies in the utility function determined by activity patterns to model route choice decisions within a daily horizon. Similar study was recently proposed by Lin et al. (2008), while Lam and Huang (2002, 2003), Polak and Heydecker (2006) and Adnan (2010) extended it to consider full trip-chaining strategies. No attempt has been made so far to include departure time choice behavior explicitly in this integration, leaving temporal decisions to only activity scheduling and still maintaining distance between the two modeling facets. In the next chapter it is discussed how novel data gathering techniques will make it possible to integrate trip distribution and activity planning. Next to the opportunities for modeling traffic, the joint analysis of trips and activities will make it possible to optimise both simultaneously for each individual traveller.

5. Opportunities for mobile phone sensor analysis

The advancement of ICT, its fast penetration in everyone's daily life and its ever growing adoption in the transportation field suggests that new and highly informative data is becoming easily available. The use of personal communication devices, like GPS and mobile communication makes it possible to collect real-time network information also on many different aspects. A straightforward way is to use them as Floating Car Data (FCD). FCD is being used to provide navigation assistants with information on actual travel times on different route segments. Because of the current availability of FCD platoons, techniques are limited to the identification of congestion on the network (Kerner, 2005). But one can envision a very near future where FCD is being used to estimate origin - destination relations and traffic intensities/densities. This is only the top of the iceberg and new possibilities are still to be explored. This chapter is completely devoted to the description of the opportunities smartphones can bring to transportation engineering.

Smartphones are carried around throughout the day by an ever growing subset of the population, and the fact that they sample the environment with different sensors on a regular basis makes them an interesting tool to extract information on travel patterns and activity behavior. The research of Bierlaire et al. (2009) shows already the possibilities to infer activity patterns from sensor measurements of Bluetooth receivers on smartphones. The registration of Bluetooth signals (but other signals as well, for example WiFi recordings, internal phone state, plugged in state, active applications) gives an indication of what kind of electronic devices are present in the surroundings.

Most applications that use Bluetooth communication are cell-phones and personal computers, but also in-car systems like navigation assistants, hands free communications and media providers. Because these applications are mainly used by only one specific user the unique code of each Bluetooth transmitter can be linked to a user, or a vehicle. The recording of all incoming signals makes it possible to estimate what kind of users are present and this allows to estimate the nature of the visit of a specific location. For example: if we record the Bluetooth devices at a working location, we record the devices of colleagues and static devices such as printers, laptops, etc. In a bar, the devices of various social groups would be recorded. If the observed devices can be linked to one or more activity types, an estimate can be made for the performed activities of a user at a specific time (Himpe, 2010). It is also possible to derive activity switches from these sensor recordings using data stream analysis (Charu C. Aggarwal, 2007).

The characteristics of the trips are also easily available. Each cell phone is aware of one or more cell phone towers in its surroundings. The phone uses this information to triangulate its geographic position. The accuracy is currently a lot lower then GPS tracking but the energy consumption is a lot lower because no additional sampling is necessary. When a phone is connected to the cell phone network an estimate for its position is immediately available. Using a series of estimates from a moving phone it is possible to accurately estimate the most likely route. Frejinger (2008) developed a modeling approach that makes the explicit matching of trip observations to the network redundant using advanced route choice algorithms.

In result, the entire daily scheme of an individual is reconstructed fully automatically. Apart from the enhanced user experience that is enabled with this information on the level of the phone, there are great opportunities for an advanced individual travel manager. Unlike traditional navigation assistants not only the optimal route will be provided but also when or how to make a trip in the most optimal conditions. The development of such a system will also increase the opportunities for managing collective transportation modes for example identifying overlapping trips and connect these travelers in the context of ride sharing or optimizing the use and availability of public transportation by grouping individuals. One of the most prominent problems will concern the privacy issues. The implementation of the applications will need to be the transparent for the user. Planning activities and optimizing trips simultaneously on the individual level, taking into account the actual traffic states, resembles the dynamic user-optimal assignment (Hoogendoorn & Bovy, 1995). Advancing along this line of thought it is possible to identify the restrictions or incentives that need to be implemented by traffic managers to make the user optimum coincide with the system optimum.

6. Conclusion

The state of the art review has highlighted a number of challenges that future research needs to tackle. First, from the point of view of DTA theory advancement and exploitation, the current simplified way of including departure time choice, i.e. without considering explicitly activity scheduling and rescheduling opportunities, hampers the assessment of management measures aiming at triggering this type of choice alternatives, and still impedes a reasonable reproduction of daily and weekly patterns. A second aspect lies in the limitations that were imposed by past data technologies, processing and analysis techniques, especially from the analysis of the activity patterns' side. The use of personal communication devices, like GPS and mobile communication makes it possible to collect real-time network information. With respect to traditional data collection methods, they are expected to be enormously cheaper and cover a growing part of the population, making statistical issues less problematic. On the other hand, entering a new era of data technologies, new calibration and validation issues are foreseen. Also reliability of information and privacy concerns will become even more crucial aspects.

Bibliography

Abdelghany, A.F. and H.S. Mahmassani (2003), *Temporal–Spatial Microassignment and Sequencing of Travel Demand with Activity/Trip Chains*. **Transportation Research Record 1831**, 248–57.

Adnan M. (2010), *Linking Macro-level Dynamic Network Loading Models with Scheduling of Individual's Daily Activity–Travel Pattern*. In Tampère C.M.J., Viti F. and Immers L.H. (Eds), **New Developments in Transport Planning – Advances in Dynamic Traffic Assignment, Edward Elgar**, Cheltenham, UK, Northampton, MA, USA.

Arentze T., Hofman F., van Mourik H. and H. Timmermans (2000), *ALBATROSS: Multiagent, Rule-Based Model of Activity Pattern Decisions,* **Transportation Research Record 1706**, 136–144.

Bierlaire, M., Hurtubia, R., and Flötteröd, G. (2009). *An experimental analysis of the implicit choice set generation using the Constrained Multinomial Logit Model*. **Proceedings of the 4th Kuhmo-Nectar Conference,** July 2 - 3, 2009.

Bhat, C.R., J.Y. Guo, S. Srinivasan and A. Sivakumar (2004), *Comprehensive Econometric Microsimulator for Daily Activity–Travel Patterns*, **Transportation Research Record 1894**, 57–66.

Bhat, C.R. and F. Koppelman (2003), *Activity-Based Modeling of Travel Demand*, **Handbook of Transportation Science,** Springer.

Bowman, J.L. and M.E. Ben-Akiva (2001), *Activity-based Disaggregate Travel Demand Model System with Activity Schedules*, **Transportation Research Part A 35(1)**, 1–28.

Caplice, C. and H.S. Mahmassani (1992), *Aspects of Commuting Behavior: Preferred Arrival Time, Use of Information and Switching Propensity*, **Transportation Research Part A 26(5)**, 409–18.

Charu C. Aggarwal**, Data Streams: Models and Algorithms (Advances in Database Systems)**, Springer-Verlag New York, Inc., Secaucus, NJ, 2006

Gärling, T., Säisä, J., Böök, A. and E. Lindberg (1986), *The spatiotemporal sequencing of everyday activities in the largescale environment*. **Journal of Environmental Psychology**, 6, 261-280.

Frejinger E. (2008), Route Choice Analysis: Data, Models, Algorithms and Applications**,** EPFL, Transport and Mobility Laboratory.

Hatcher, S.G. and H.S. Mahmassani (1992), *Daily Variability of Route and Trip Scheduling Decisions for the Evening Commute*, **Transportation Research Record 1357**, 72–81.

Heydecker, B.G. and J.D. Addison (1998), *Analysis of Traffic Models for Dynamic Equilibrium Traffic Assignment*, In M.G.H. Bell (ed.), **Transportation Networks: Recent Methodological Advances**, Pergamon, Oxford, UK, 35–49.

Himpe W. (2010), **Combining heterogeneous sensor information for the activity tracking of smartphone users**, K.U.Leuven, Departement Bouwkunde.

Hoogendoorn S.P., Bovy P.H.L., *Dynamic user-optimal assignment in continuous time and space*, **Transportation Research Part B 38(7)**, August 2004, Pages 571-592

Kerner, B. S., C. Demir, R. G. Herrtwich, S. L Klenov, H. Rehborn,M. Aleksić, A. Haug,

DaimlerChrysler AG (2005), *Traffic State Detection with Floating Car Data in Road Network.* **Proceedings of the 8th International IEEE Conference on Intelligent Transportation Systems,** Vienna, Austria, September 13-16, 2005

Khattak, A.J., J.L. Schofer and F.S. Koppelman (1995), *Effect of Traffic Information on Commuters' Propensity to Change Route and Departure Time*, **Journal of Advanced Transportation 29(2)**, 193–212.

Kitamura R., Pas E.I., Lula C.V., Lawton T.K. and P.E. Benson (1996), *The sequenced activity mobility simulator (SAMS): an integrated approach to modeling transportation, land use and air quality*, **Transportation 23**, 267 – 291.

Lam, W.H.K. and H.-J. Huang (2002), *A Combined Activity–Travel Choice Model for Congested Road Networks with Queues*, **Transportation 29(1)**, 5–29.

Lam, W.H.K. and H.-J. Huang (2003), *Combined Activity/Travel Choice Models: Time-Dependent and Dynamic Versions*. **Networks and Spatial Economics 3(3)**, 323–47.

Lam W.H.K. and Yin Y. (2001), *Activity-based Dynamic Traffic Assignment Model*, **Transportation Research Part B 35**, 549-574.

Lim, Y. and B. Heydecker (2005), *Dynamic Departure Time and Stochastic User Equilibrium Assignment*, **Transportation Research Part B 39(1)**, 97–118.

Lin D.-Y., Eluru N., Travis Waller S. and Bhat C.R. (2008), *Integration of Activity-Based Modeliing and Dynamic Traffic Assignment*. **Transportation Research Record 2076**, 52-61.

Mannering, F. (1989), *Poisson Analysis of Commuter Flexibility in Changing Routes and Departure Times*, **Transportation Research Part B 23(1)**, 53–60.

Mahmassani H.S. and Y.-H. Liu (1999), *Dynamics of Commuting Decision Behavior under Advanced Traveler Information Systems*, **Transportation Research Part C 7**, 91–107.

McNally M.G. (2000), *The Activity-based Approach*, In Hensher D.A. and Button K.J. (Eds), **Handbook of Transport Modelling**, Elsevier, Amsterdam, The Netherlands.

Polak, J.W. and B.G. Heydecker (2006), *The Dynamic Assignment of Tours in Congested Networks with Pricing*, **Proceedings of the 1st DTA Symposium**, Leeds, U.K.

Recker, W.W., McNally, M.G. and Root, G.S., 1986a, *A model of complex travel behaviour: Theoretical development*. **Transportation Research 20A**, 307-318.

Recker, W.W., McNally, M.G. and Root, G.S., 1986b, *A model of complex travel behaviour: An operational model*. **Transportation Research 20A**, 319-330.

Sheffi, Y. and C.F. Daganzo (1979), *Hypernetworks and Supply–Demand Equilibrium Obtained with Disaggregate Demand Models*, Transportation Research Record 673, 113–21

Small, K.A. (1982), *The Scheduling of Consumer Activities: Work Trips*. **American Economic Review 72(3)**, 467–79.

Szeto, W.Y. and H.K. Lo (2004), *A Cell-based Simultaneous Route and Departure Time Choice Model with Elastic Demand*, **Transportation Research Part B 38(7)**, 593–612.

Van der Zijpp, N.J. and C.H.R. Lindveld (2001), *Estimation of Origin Destination Demand for Dynamic Assignment with Simultaneous Route and Departure Time Choice*, **Transportation Research Record 1771**, 75–82.

Viti, F., E.A.I. Bogers and S.P. Hoogendoorn (2005), *Day-to-day Learning under Uncertainty and with Information Provision: Model and Data Analysis*, Presented at the **16th International Symposium of Transport and Traffic Theory (ISTTT16)**, University of Maryland, Maryland.

Viti F., Tampère C.M.J, (2010), *Dynamic Traffic Assignement: Recent Advances and New Theories Towards Real Time Applications and Realistic Travel Behaviour (Editorial)*. In Tampère C.M.J., Viti F. and Immers L.H. (Eds), **New Developments in Transport Planning – Advances in Dynamic Traffic Assignment, Edward Elgar**, Cheltenham, UK, Northampton, MA, USA.

Zwerts E. (2004), *Activity-based Modeling: An Overview*. **Presented at the GRT Seminairie**, October 2004, University of Namur, Belgium.